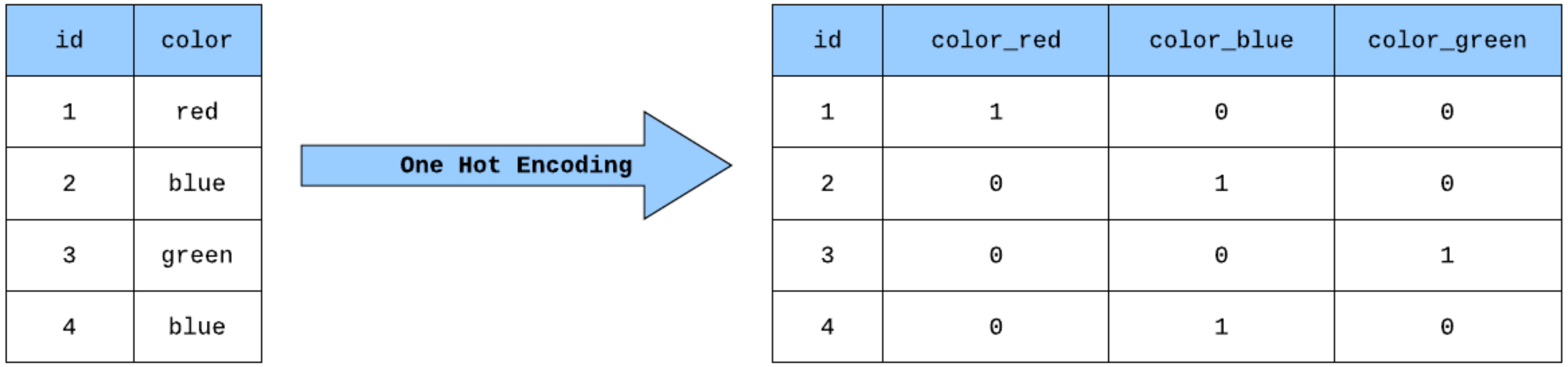
Introduction to Word Embeddings

307307 BI Methods

Converting Words to Numbers

Old Method:- One-Hot Encoding
Each word is represented by setting one dimension to 1 and all the other dimensions to ZEROS.


One Hot Encoding

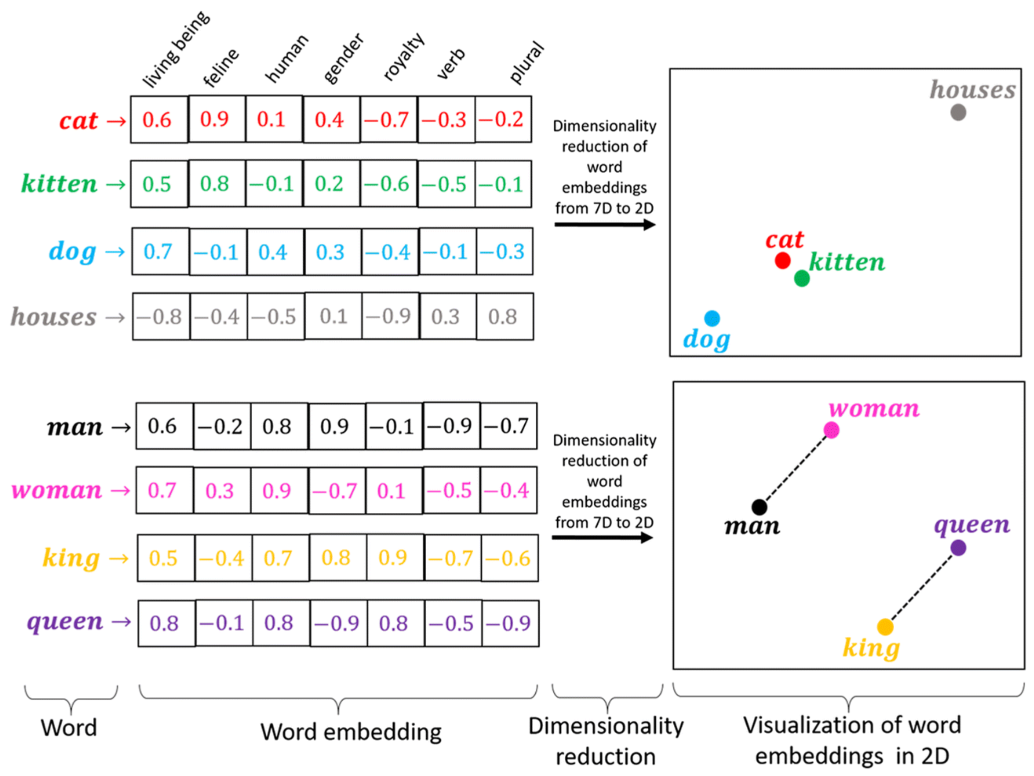
id	color
1	red
2	blue
3	green
4	blue

id	color_red	color_blue	color_green
1	1	0	0
2	0	1	0
3	0	0	1
4	0	1	0

Limitations:
- Vocabulary of 100,000 words → 100,000 dimensions [0010000000000000000000000000000000000000…etc.]
- All words equally distant from each other
- No semantic meaning captured

Word Embeddings and Vector Spaces

- Words are encoded as dense numerical vectors instead of one-hot or sparse representations.
- Similar words → similar vectors
- Typically, 50-300 dimensions (vs. vocabulary size in 1-hot-encoding)
- Word Embeddings captures semantic and syntactic relationships about/between words.
- Each dimension potentially captures some syntactic or semantic meaning.
- These vectors are learned from text by models like Word2Vec.


Dimensionality reduction of word embeddings from 7D to 2D
houses
cat
kitten
dog
Dimensionality reduction of word embeddings from 7D to 2D
woman
man
queen
king
Word
Word embedding
Dimensionality reduction
Visualization of word embeddings in 2D

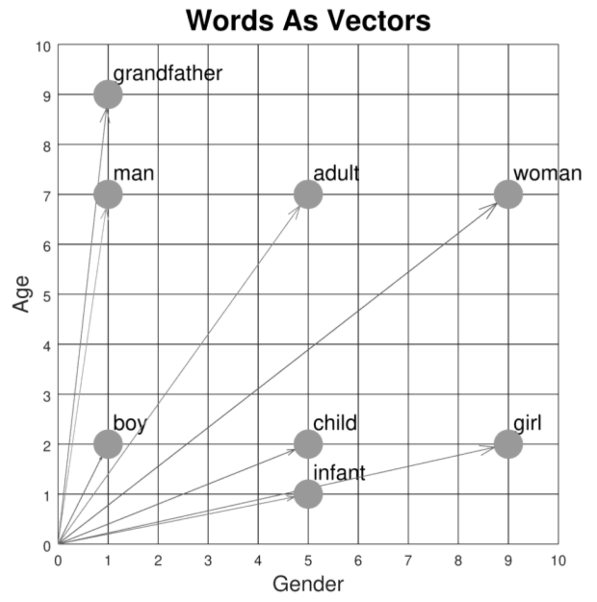
	living being	feline	human	gender	royalty	verb	plural
cat →	0.6	0.9	0.1	0.4	−0.7	−0.3	−0.2
kitten →	0.5	0.8	−0.1	0.2	−0.6	−0.5	−0.1
dog →	0.7	−0.1	0.4	0.3	−0.4	−0.1	−0.3
houses →	−0.8	−0.4	−0.5	0.1	−0.9	0.3	0.8
man →	0.6	−0.2	0.8	0.9	−0.1	−0.9	−0.7
woman →	0.7	0.3	0.9	−0.7	0.1	−0.5	−0.4
king →	0.5	−0.4	0.7	0.8	0.9	−0.7	−0.6
queen →	0.8	−0.1	0.8	−0.9	0.8	−0.5	−0.9

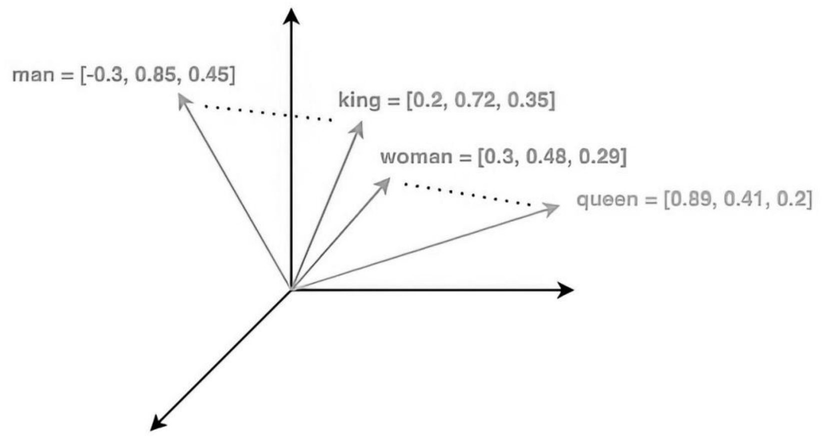
Vector Spaces and Word Embeddings

- A vector space is a mathematical space where each word is represented as a point (or vector) in multi-dimensional space.
- Makes it possible to compare, visualize, and manipulate meanings of words using math.
- Enables operations like:
  - Similarity: "king" is close to "queen"
  - Analogy: "king" - "man" + "woman" ≈ "queen"

Properties of Vector Space

- Semantic relationships are preserved (e.g., “man" is closer to “grandfather" than “girl").
- Closer Vectors → Similar Meanings
- Vectors Farther Apart → Dissimilar Meanings





Key Intuition

- Distributional hypothesis - "You shall know a word by the company it keeps" (J.R. Firth, 1957)
- Words in similar contexts have similar meanings:
- "The **cat** sat on the mat"
- "The **dog** sat on the mat"
- "The **rabbit** sat on the mat"
- → cat, dog, rabbit learn similar representations

Word2Vec (Tomas Mikolov et al., 2013)

Word2Vec was developed by Tomas Mikolov and team at Google.

Mikolov presented two architectures:

1) CBOW (Continuous Bag of Words): Predict word from context

- Input: [the, ___, sat, on] → Output: cat

2) Skip-gram: Predict context from word

- Input: cat → Output: [the, sat, on, mat]

- Trained on massive text corpora using simple neural networks

Mikolov Approach – Convert Text into Input-Output Pairs

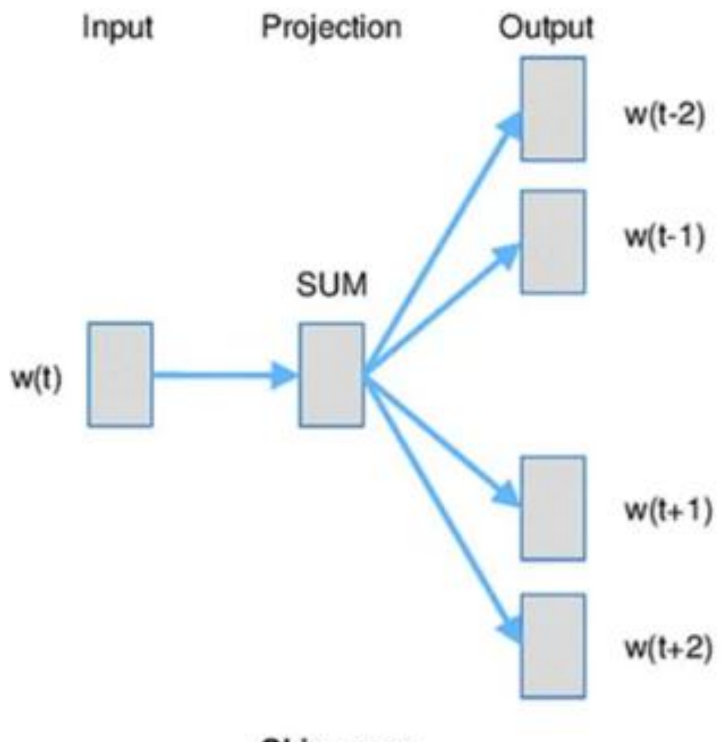
Suppose we have these sentences (corpus), we can convert them into input output pairs to be used for training a neural network:

Large language models are transforming business applications by introducing new levels of automation, intelligence, and personalization across industries. These models, trained on vast amounts of text data, can understand and generate human-like language, allowing businesses to enhance customer interactions, streamline operations, and gain deeper insights from data. In customer service, for instance, large language models power advanced chatbots and virtual assistants that can handle complex queries, provide 24/7 support, and adapt to customer needs in real time. In marketing, they help craft personalized messages, analyze consumer sentiment, and optimize content strategies with remarkable precision. Organizations are also using these models to automate report generation, summarize large documents, and even assist in writing code or drafting legal documents, significantly reducing time and cost. Moreover, they enable better decision-making by turning unstructured data—such as emails, reviews, or social media posts—into actionable business intelligence. As companies integrate these tools, they not only boost productivity but also redefine how humans and machines collaborate in the workplace. However, this transformation also raises questions about data privacy, ethical AI use, and workforce adaptation, making responsible deployment as important as technological innovation itself.

Skip-gram Architecture

- **Source Sentence:** "Large language models are transforming business applications"
- **Window Size:** 2 (2 words on each side of target word)
- **Task:** Predict context words from target word
- Given Target Word Predict → Context Words

Input (Target Word)	Output (Context Words)
Large	[language, models]
language	[Large, models, are]
models	[Large, language, are, transforming]
are	[language, models, transforming, business]
transforming	[models, are, business, applications]
business	[are, transforming, applications]
applications	[transforming, business]

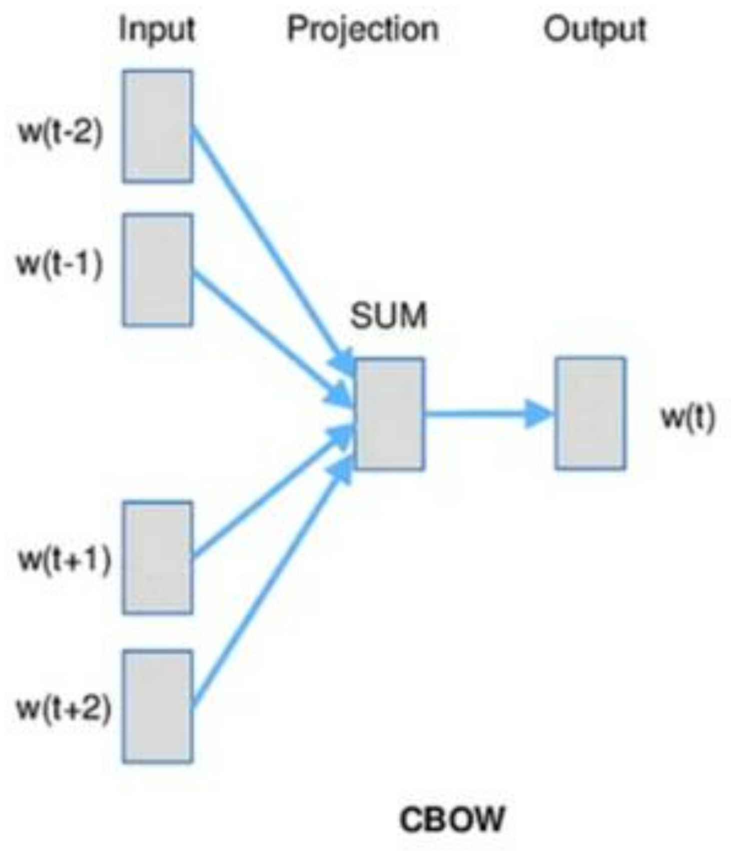


Skip-gram

CBOW (Continuous Bag of Words) Architecture

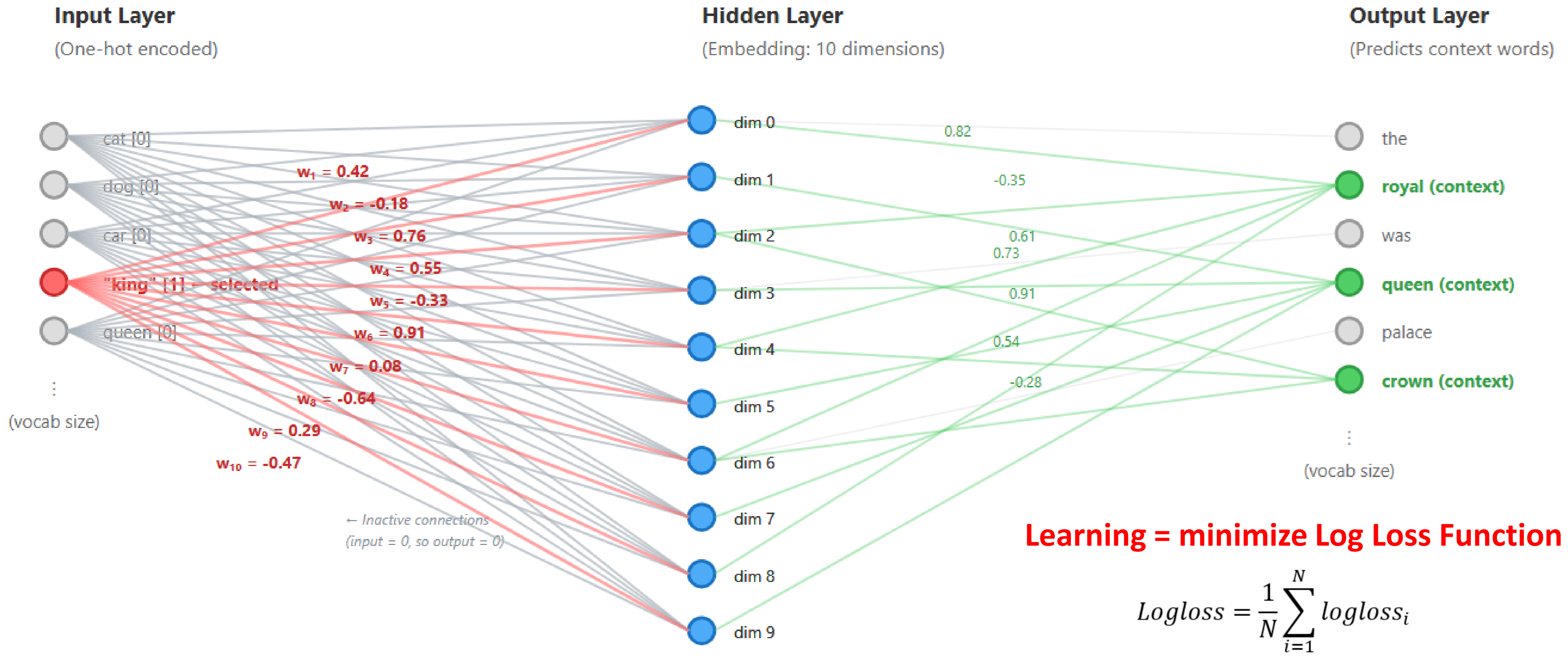
- **Source Sentence:** "Large language models are transforming business applications"
- **Task:** Predict target word from context words
- Given Context Words Predict → Target Word

Input (Context Words)	Output (Target Word)
[language, models]	Large
[Large, models, are]	language
[Large, language, are, transforming]	models
[language, models, transforming, business]	are
[models, are, business, applications]	transforming
[are, transforming, applications]	business
[transforming, business]	applications



Word2Vec Skip-gram: Learning Word Embeddings

Training sentence: "The **king** wore a royal crown, and the queen stood beside him"



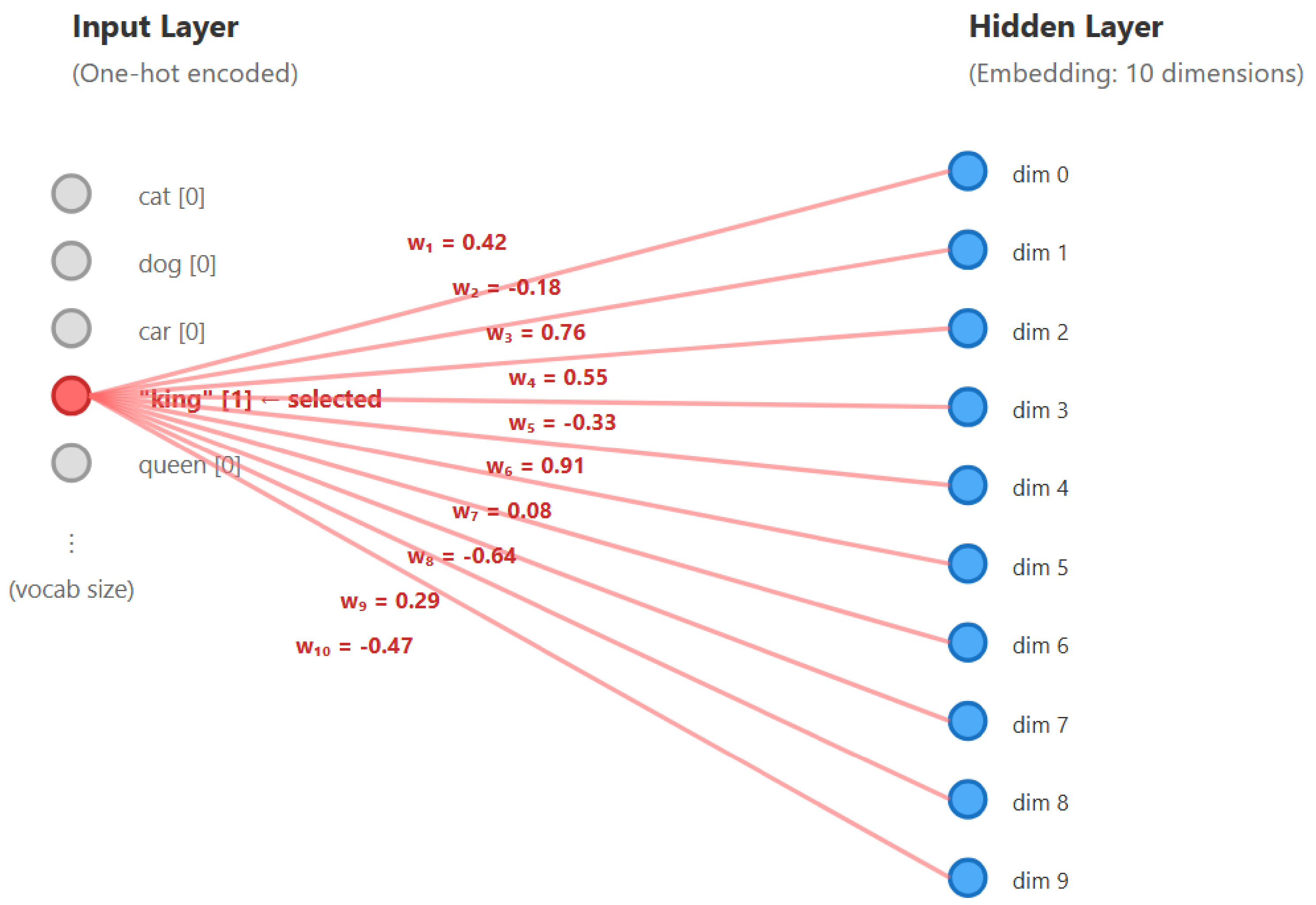
Learning = minimize Log Loss Function

$$Logloss = \frac{1}{N}\sum_{i=1}^{N} logloss_i$$

Training Process: Input Word "king" → Embedding → Predict Context Words

- Input→Hidden weights = Word Embeddings (e.g., king = [0.42, -0.18, 0.76, 0.55, -0.33, 0.91, 0.08, -0.64, 0.29, -0.47])
- Hidden→Output weights predict context: Given "king", maximize probability of "royal", "queen", "crown"
- Backpropagation updates both weight matrices → words in similar contexts get similar embeddings

Skip-Gram Model



Core Math Behind Word2Vec: Softmax & Log-Loss

- **Softmax:** converts raw scores into probabilities

$$P_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

Example: suppose the model gives raw scores $[2, 1, 0.1]$. Softmax turns these into probabilities $[0.66, 0.24, 0.10]$, so the highest score becomes the highest probability, and all probabilities sum to 1.

- **Log loss (or cross-entropy loss):** measures how well the predicted probabilities match the correct answer

$$L = -\log(P_{\text{correct}})$$

Example:

- If $P_{\text{correct}} = 0.9$, then $L = -\log(0.9) \approx 0.11$
- If $P_{\text{correct}} = 0.1$, then $L = -\log(0.1) \approx 2.30$

Higher probability for the correct word gives a smaller loss, and lower probability gives a larger loss.

Measuring Similarity Between Word Vectors

Why Compare Word Vectors?

- Word embeddings map words into a vector space.
- **Words with similar meanings** are placed **close together** in that space.
- To quantify this "closeness," we use **vector similarity**.

Cosine Similarity

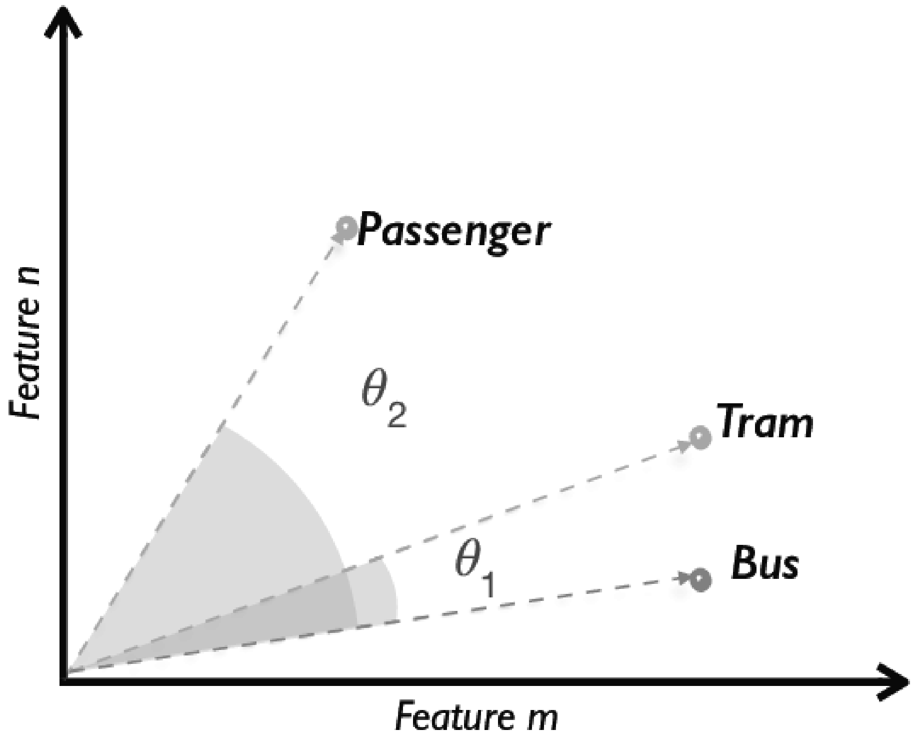
Most common metric used to compare word vectors:

$$\text{cosine\_similarity}(\vec{A}, \vec{B}) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \|\vec{B}\|}$$

- Measures the **angle** between two vectors (not their magnitude).
- Ranges from **-1 to 1**:
  - 1 → Same direction (very similar)
  - 0 → Orthogonal (unrelated)
  - -1 → Opposite directions (very different)

Intuition

- Vectors for `"king"` and `"queen"` will have high cosine similarity.
- Vectors for `"apple"` and `"keyboard"` will have low similarity.



Use Pre-Trained Embeddings

Gensim is an open-source Python library used for **topic modeling** and **natural language processing (NLP)**.
It's great for working with **large text datasets** because it doesn't need to load all the data into memory at once.

Key features:

- Builds and uses **word embeddings** (like Word2Vec, FastText, Doc2Vec).
- Measures **semantic similarity** between words or documents.
- **Efficient and memory-friendly**, ideal for handling big collections of text.

```
import gensim.downloader as api
from gensim.models import Word2Vec

# Load pre-trained Word2Vec model
word2vec_model = api.load("word2vec-google-news-300")


# Get vector for a word
cat_vector = model.wv['cat']
print("Vector for 'cat':", cat_vector[:5])  # Show first
5 dimensions

# Find similar words
similar_words = word2vec_model.most_similar('computer',
   topn=5)
print("Words similar to 'computer':", similar_words)

# Word analogies
result = word2vec_model.most_similar(positive=['woman',
   'king'], negative=['man'], topn=1)
print("king - man + woman =", result)
```

Open in Colab

Applications of Word Embeddings in NLP

1. **Semantic Similarity**
   Measure how similar two words, phrases, or documents are by comparing their vector representations.
   Example: Identifying that "doctor" and "physician" are closely related.
2. **Text Classification**
   Used as input features for tasks like spam detection, sentiment analysis, and topic classification.
   Embeddings provide rich, dense input for machine learning models.
3. **Named Entity Recognition (NER)**
   Help identify proper nouns and classify them into categories like person, location, or organization.
   Embedding-based models improve contextual understanding of named entities.
4. **Machine Translation**
   Map words from one language to another by aligning embeddings in multilingual space.
   Improves translation accuracy by leveraging semantic proximity.
5. **Question Answering & Chatbots**
   Used to understand queries and match them with appropriate answers or responses.
   Enable bots to interpret intent and context more accurately.

- **6. Information Retrieval**
  Enhance search engines by retrieving results based on semantic meaning, not just keyword matches.
  Example: Searching for “heart attack” returns documents containing “cardiac arrest.”